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SYSTEM RELIABILITY ESTIMATION WITH INPUT DATA FROM DETERMINISTIC SIMULATIONS

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ABSTRACT

The possibility of estimating reliability of hardware, both for components and systems, is important in engineering design, since many failures result in substantial impact on safety or functional requirements. Existing reliability estimation methods require measured or estimated input data which can be difficult to retrieve. The objective of this paper is therefore to derive a simulation-driven method, including variation management, for combining deterministic simulations with Fault Tree Analysis, to estimate system reliability when measured data is not available.

The research work started with a literature survey followed by description of a typical as-is situation and definition of a to-be scenario. Then, a simulation-driven method was derived and verified by a case study. In particular, the system used for the case study was modeled and simulated as a transient dynamical system to derive information about loads on components. It was found that deterministic simulations can be used to produce relevant input data for fault tree analysis. The derived simulation-driven system reliability estimation method includes variation management and can be used for evaluation of concepts in the early stages of product development when limited measurement data is available.

1 INTRODUCTION

The possibility of estimating reliability of hardware, both for components and systems, is important in engineering design, since many failures result in substantial impact on safety or functional requirements resulting in expensive reclamations and dissatisfaction that may lead to loss of income.

The reliability of individual components is superior to the corresponding system reliability [1]. In 1961, Weibull [2] formulated a distribution (the Weibull distribution) which is one of the most commonly used formulas for describing important

probabilistic measures in reliability theory, e.g. times to failures, extreme values, service life and requirements allocation.

Today, there exist several methods for predicting the reliability of hardware systems and for how to identify causes of failure and failure modes, e.g. Fault Tree Analysis (FTA) [3, 4] and Failure Mode and Effect Analysis (FMEA) [4, 5]. In FTA and FMEA, information about the consequences and effects of failures and failure modes is usually collected through interviews with experienced people, from different divisions, with different knowledge, i.e. cross-functional groups [6]. Fault tree analysis (FTA) is a deductive method, i.e. a general system state is postulated and decomposed into chains of more basic events (faults) of components [7]. The logical interrelationship of how such basic events depend on and affect each other, and thereby cause some system state to occur, is often described analytically in a reliability structure which can be visualized as a tree. Since many failures are caused by variations (strength, loads, manufacturing tolerances, etc.), industries are in need of robust design methodologies that can be used to identify and manage different sources of variation [8, 9]. Therefore, a method called Variation Mode and Effect Analysis (VMEA) has been developed. VMEA is a top-down method for identification and management of sources of variation [10, 11] and reliability prediction of hardware systems [12]. FTA, FMEA and VMEA can be used in different phases of the product development process, depending on whether the developed system is completely new or is an upgraded system [13].

Ruppert and Bertsche [14] proposed a method for combining qualitative reliability analysis with quantitative methods. They further integrated reliability analysis with a computer-aided design (CAD) process throughout all stages of product development for a limited number of system components. The failure behavior of the mechanical parts was determined using a

three-parametric Weibull distribution and a practical application of a Boolean serial model and fault tree analysis (FTA) [14].

Design for reliability and built-in reliability, i.e. effective measures to create robust designs and manufacturing processes, can be achieved through modeling of failure processes and proactive work early in product development. A statistical virtual experimental design has been developed, based on finite element models of key structures in systems, including the geometrical and materials variables comprising the system and a fatigue prediction model. Information for process development or improvement derived from the virtual experiment is embedded in a Monte Carlo simulation to assess the impact of uncertainty and variability [15]. A similar methodology has been developed to predict the reliability of a product at an early stage in the development process [16]. This methodology integrates Finite Element Models (FEM) with statistical methods such as Design of Experiments (DOE) and Response Surface Models (RSM) that generate the input parameters used in Finite Element Analysis. Failure probability was calculated by using Monte Carlo simulations

Bearing models have been developed to determine the vibration response of general rotor-bearing systems, enabling identification of sets of parameters resulting in undesirable vibrations due to bearing nonlinearity [17]. Models and methods for estimation of bearing fatigue limit stress [18] and defect-propagation models for remaining utility estimation of defect bearing have also been developed [19].

Today, measured data or estimated data is often used as input to such reliability prediction methods. However, when designing new systems, such measurement data may not exist. Hence, in order to conduct measurements to retrieve such data a prototype needs to be manufactured, which often requires a significant amount of time. In such situations, deterministic simulations could possibly be used to derive the needed input data, which is the scope for this paper. By use of simulations, concepts can be evaluated by means of reliability in early stages of the product development process, i.e. before a physical prototype is manufactured. Variations in raw material properties, production outcome and assembling tolerances, etc. result in system variations which must be managed.

Hence, the objective is to derive a simulation-driven method, including variation management, for combining deterministic simulations with Fault Tree Analysis, to estimate system reliability when measured data is not available.

The hypothesis is that component failure rate can be estimated by use of deterministic simulations and used as input data to Fault Tree Analysis. The result from the Fault Tree Analysis can then serve as a basis for designing components and systems for improved reliability.

2 RESEARCH APPROACH

The research presented in this paper began with a literature review regarding reliability estimation methods, variation management and methods for how to derive information

needed for such analyses. To further highlight gaps that must be overcome and to guide the research work, a typical as-is situation was described and a to-be scenario was developed forecasting a possible future situation. Based on this to-be scenario, a new simulation-driven method is proposed, whereby deterministic simulations are used to provide necessary information to probabilistic reliability methods, hence enabling estimation of reliability for new concepts where failure data is lacking. To verify the suggested method a case study of a rotor dynamical example was conducted.

3 AS-IS SITUATION AND TO-BE SCENARIO

Today, FTA is a commonly used method for evaluation of hardware reliability. For each failure mode, besides the reliability structure, the failure rate of the components is required (this assumes that the component has a constant failure rate and that failure times are given by the exponential distribution). Hence, in order to retrieve the data necessary to conduct FTA, knowledge about existing failure modes and their causes is required, i.e. logical relationships that cause faults to propagate from components to system level.

3.1 AS-IS SITUATION

When upgrading existing systems, FTA is usually not a problem, since the failure modes and failure rates of the old system are often documented and can to some extent be transferred to the upgraded system. On the other hand, when developing completely new solutions, failure mode data and failure rates may not be available; today, this is often managed through estimations. Even for existing systems, all required data is seldom available, in which case interviews often are conducted, which may require some time (and may also introduce a risk of retrieving incorrect data). For large systems, since one fault tree is needed for each failure mode, it may be time consuming to derive the fault tree itself (since the reliability structure might be quite complex).

3.2 TO-BE SCENARIO

In a future scenario, when performing FTA of completely new concepts, i.e. where little or no data for such analyses exists, as much required information as possible is derived through simulations. Commonly, the design of hardware systems is carried out by use of some computer-aided design (CAD) software. In this to-be scenario the reliability structure, including all relevant failure modes, is automatically generated from the assembly structure designed in the CAD software. In this scenario, the assembly structure serves as a base to preprocess simulation models from which transient loads on the components included in the reliability structure can be estimated. There are several variation sources between the design stage of the product development process and the finally manufactured hardware (tolerances in raw material properties, tolerances in drawings, variations during manufacturing, etc.). Such variations are in this scenario accounted for in the deterministic transient simulations, which then give component failure rates. With a known reliability structure and coupled

component failure rates regular FTA can finally be conducted to derive the hardware system reliability.

4 SIMULATION-DRIVEN RELIABILITY ESTIMATION METHOD

In order to reach the to-be scenario described in section 3.2, there are several enablers needed. In this paper, the focus is on how to derive the failure rates through simulations, given that the reliability structure is known. In order for such simulations to provide added value, compared to as-is methods, the accuracy of the input data to the FTA must increase. This requires valid deterministic simulation models with low uncertainty in the preprocessing parameters and solving parameters.

The proposed simulation-driven method can be divided into five steps, see Fig. 1.

Figure 1. Proposed simulation-driven method

No series produced products are identical. On the contrary, such products always include variations in geometry, material properties, strength, ductility, load intensity, etc., each with some variation distribution function. During the *Parameter Variation* step of the proposed simulation-driven method variations, i.e. distribution functions in the manufactured product are traced.

In order to derive the information needed for FTA, *deterministic models* coupled to each failure mode are developed, e.g. finite element models, multi body dynamical models, fluid dynamical models, etc.

The variation distributions are then mapped to the deterministic model preprocessing parameters. Then, based on these distributions, several sets of parameters are *randomly* generated, i.e. each set of parameters representing one possible manufactured system. If the number of significant variations is large, some suitable method for selecting the most important ones can be deployed, e.g., design of experiments, etc.

All the different models are then solved numerically for every set of parameters to derive the transient loads on each component. Known load on the components, together with strength, enables derivation of the component durability. Durability is an aspect of reliability, related to the ability of a component to withstand the effects of time, travelled distance, operating cycles/hours, etc. One component can have several failure modes due to different causes of failure, e.g. due to fatigue, overload, wear, corrosion, etc. Durability is usually expressed as a minimum time before the occurrence of wear-out failures. Hence, in the third step of the proposed method, for each deterministic model (each set of preprocessing parameters) the durability of each failure mode is derived using the transient loads and the component strength. For every failure mode, the durability of every deterministic model is listed and hence, when the number of models is large enough, the *failure rates* can be determined. If no failure modes that corresponds to initial failures and ageing failures exist, these failure rates corresponds to the useful life part of the bathtub curve, see Fig. 2.

Figure 2. Bathtub curve

Finally, when the failure rates and the fault tree are known, a regular *FTA* can be conducted in order to derive the system reliability.

5 CASE STUDY

To verify the proposed reliability estimation method a case study on rotating machinery was conducted. This machine is an overhung rotor system supported on two roller bearings mounted on two pedestals. For simplicity reasons, it is assumed that the corresponding fault tree consists of two failure modes, both coupled to bearing failure. If one bearing fails the system fails, giving the fault tree shown in Fig. 3.

A complete simulation on this system should include all failure modes for the system, e.g. shaft fracture, rotor fatigue, loss of torque, etc. Deterministic models and simulations coupled to each failure mode should then have to be performed to derive the failure rates needed for the FTA to derive the system reliability.

Figure 3. Fault tree of rotating machinery

Variation Properties

In this paper, for simplicity reasons, it is assumed that all system properties are constants except for the bearing clearance, which is assumed to have a normal distribution with mean value (MVL) 0.1 mm and a standard deviation (STD) of 0.01 mm.

Deterministic Modeling

In order to determine the transient loads acting on the bearings a rotor dynamical model was developed, see Fig. 4.

Figure 4. The rotor bearing model

In this simplified model, the shaft was meshed by 2 Euler beam elements with the degrees of freedom x , y , ϕ and θ at each node (while a more accurate model probably would have required more elements). Hence, the system has 3 nodes and 12 degrees of freedom, where node 1 is the leftmost node in Fig. 4 where the *rear bearing* is positioned. The *front bearing* is positioned in node 2, i.e. at the middle node in Fig. 4 and Disc 1 (the rotor) is positioned at node 3, i.e. at the rightmost node in Fig. 4. The xy -plane is perpendicular to the rotational symmetric z -axis, ϕ is rotation around the x -axis and θ rotation around the y -axis. In the model, gravity is applied in y -direction (volume load) and the rotor is subjected to rotational load with spin speed frequency due to a mass unbalance (See Unbal. 1 in Fig. 4), i.e. the rotor mass is positioned a short distance away from the rotor center. Parameters of the Shaft, Rotor, Pedestals and load of the rotor system model are given in Table 1, i.e. preprocessing parameters.

Table 1. Parameters of rotor system

SHAFT		ROTOR	
Density (kg/m ³)	7800	Shaft position (m)	Node 3
Young's Modulus (GPa)	200	Mass (kg)	2000
Length (m)	1	Polar mass moment of inertia (kgm ²)	300
Radius (m)	0.1	Transversal mass moment of inertia (kgm ²)	600
PEDESTALS		LOAD	
Shaft Position (m)	0 0.8	Rotor Unbalance (m)	1e-3
type	Radial bearing with clearance	Gravity (m/s ²)	10
Isotropic Stiffness (N/m)	1e11 1e11	Spin Speed (Hz)	20
MVL Clear (m)	0.0001		
STD Clear (m)	0.00001		

Proportional damping is used, i.e. the damping matrix $\mathbf{C} = \alpha[\mathbf{M}] + \beta[\mathbf{K}]$ where $\alpha = 200$ and $\beta = 1 \cdot 10^{-8}$, which results in a range of damping ratio between 0.25% and 14% when considering all vibration modes (when the clearance vanishes). In this scenario it is assumed that all parameters shown in Table 1 are held constant except for the clearance.

Randomization

In this case it is assumed that only the clearances in the roller bearings are subjected to variations. Here, 2000 sets of parameters (in this case clearance) are generated randomly based on the normal (Gaussian) distribution. A normal distribution is often used as a first approximation to describe real valued random variables that cluster around a single mean value. The distribution for the clearance in the rear bearing and the front bearing are shown in Fig. 5.

Figure 5. Clearance distribution in bearings

Failure Rate Estimation

In order to derive the failure rates for each of the bearings the bearing load for each set of parameters generated in the randomization step must be estimated. Therefore, rotor dynamical simulations for each set of parameters were conducted through a fourth-order Runge Kutta algorithm with a time step of $1 \cdot 10^{-6}$ s. Figure 6 shows the vibration orbit in the rear bearing at 20 Hz spin speed.

Figure 6. Vibration orbit in the rear bearing at 20 Hz spin speed

The vibrations result in radial forces on the bearing that affect the durability. Figure 7 shows the radial force on the rear bearing at 20 Hz spin speed.

Figure 7. Radial force on rear bearing at 20 Hz spin speed

When the load on the bearing is known, the durability value L_{10h} for each failure mode is derived by using the affected load and component strength for the bearing. L_{10h} (basic rating life at 90% reliability, operating hours) is a measure of the durability for a population of components or system of components, in the form of rating life/ hours in use. L_{10h} is a time measure at which 10% of components or systems of components have failed. Failure rate is the frequency of component or system components failures, commonly expressed in failures per hour. The failure rate of a component or system of components usually depends on time, with the rate varying over the lifecycle of the system. In this case study, the spin speed is constant, giving an opportunity to express the rating life in terms of operating hours or number of revolutions. In this case study the rating life formula of a bearing is used for durability calculation, i.e.

$$L_{10} = (C/P)^p \quad (1)$$

and

$$L_{10h} = 10^6 / 60n L_{10} \quad (2)$$

where

L_{10} represents the basic rating life (at 90% reliability) [millions of revolutions], L_{10h} the basic rating life (at 90% reliability) [operating hours], C the basic dynamic load rating [kN], P the equivalent bearing load [kN], n the rotational speed/spin speed [r/min] and p the exponent of the life equation [20].

In this case study the bearings are of type SKF NU 1040 MA with properties according to Table 2. NU 1040 MA is a single-row cylindrical roller bearing provided by the bearing manufacturer SKF. [21].

Table 2. Properties for L_{10h} calculation

BEARING TYPE	SKF NU 1040 MA
C [kN]	380e6
P [kN]	Radial force derived from the rotor dynamical model
n [r/min]	1200
p [-]	10/3

Since the bearing load varies significantly with time load, spectrums for each set of parameter are generated.

Figure 8. Bearing load spectrum for the rear bearing

Figure 8 shows the load histogram at the rear bearing for one of the 2000 different sets clearances. The x-axis shows load (divided in blocks) and y-axis shows load level distribution within each load block.

Heavy and medium loads have a larger impact on component durability than small loads. Therefore, it is important to capture shock and peak, even if the occurrence of these loads can be rare and is limited to a few revolutions. Within each block the bearing load is averaged to a constant value, P_n , and lifecycle fraction under the condition is based on percentage of operation, U_n , during the same block.

The bearing life estimation for durability calculation under variable operating condition,

$$L_{10m} = \frac{1}{\frac{U_1}{L_{10m1}} + \frac{U_2}{L_{10m2}} + \dots + \frac{U_n}{L_{10mn}}} \quad (3)$$

is used in this case study where

L_{10m} represents the SKF rating life (at 90% reliability) [millions of revolutions], L_{10mn} the fraction SKF rating lives (at 90% reliability under constant conditions) [millions of revolutions] and U_n the lifecycle fraction under the condition (percentage of operation) [20].

The bearing load spectrum shown in Fig. 8 combined with Eq. (1), (2) and (3) gives the bearing durability value L_{10mh} , rating life (at 90% reliability) [operating hours]. At L_{10mh} , 10% of the components with that particular clearance combination have failed. Hence, some model for when these and the other 90% of components fail could be applied, thereby giving more statistical data to be used for failure rate calculations. However, for simplicity reasons in this case study, the L_{10mh} is directly used as a measure of one component failure. Figure 9 shows the L_{10mh} failure distribution at the rear bearing from the 2000 simulations.

Figure 9. Number of L_{10} failures at different times for rear bearing

Figure 10 shows the L_{10mh} failure distribution at the rear bearing from the 2000 simulations.

Figure 10. Number of L_{10} failures at different times for front bearing

When the failure distribution is known (see Fig. 9) the failure rate

$$\lambda = \frac{N_f(t + dt) - N_f(t)}{(N - N_f(t)) dt} \quad (4)$$

where N_f is the cumulative failures, N is the total failures, t is operating hour and dt the histogram time block size [4]. Figure 11 shows the estimated failure rate function for the rear bearing and Fig. 12 the estimated failure rate function for the front bearing.

Figure 11. Failure rate rear bearing

Figure 12. Failure rate front bearing

The rear bearing carries less load than the front bearing, which therefore has a higher failure rate. The front bearing limits the durability, hence the system reliability until 12000h (see fig. 12) is of interest. In this time span the constant failure rates

$$\lambda_r \approx 0 \quad (5)$$

$$\lambda_f \approx 5 \cdot 10^{-6} \quad (6)$$

are assumed for the rear (λ_r) and the front bearing (λ_f).

FTA

The fault tree consists of two failure modes, shown in Fig. 3, both coupled to bearing durability failure. The probability of failure

$$Q(t) = (1 - e^{-\lambda_r t}) + (1 - e^{-\lambda_f t}) - (1 - e^{-\lambda_r t})(1 - e^{-\lambda_f t}) \quad (7)$$

for the fault tree in this case study, hence the reliability

$$R(t) = 1 - Q(t) \quad (8)$$

Combining Eqs. (5) and (6) into Eqs. (7) and (8) then gives the system reliability for the case study

$$R(t) = e^{-\lambda_r t} + e^{-\lambda_f t} - 1 + (1 - e^{-\lambda_r t})(1 - e^{-\lambda_f t}) \quad (9)$$

Eqs. (5) and (6) into Eq. (9) gives the estimated system reliability $R(t) = e^{-5 \cdot 10^{-6} t}$, which is valid until 12000 operating hours.

CONCLUSIONS

In this paper, a five-step simulation-driven method combining deterministic models and probabilistic methods for estimating system reliability has been proposed based on a to-be scenario. In this method, variation properties (distribution, standard deviation, etc.) are randomized and then considered in deterministic models.

Through the case study, it was found that deterministic simulations can be used to generate failure rates to be used in fault tree analysis for reliability estimations. The proposed method takes different variations into account, e.g. due to manufacturing, differences in raw material, assembling, etc. Since the proposed method only requires information regarding variation distributions and fault mechanics, it is appropriate for use during evaluation of concepts in early product development stages when limited measured data is available. Hence, it is plausible that the proposed method can limit testing procedures during product development.

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